An Intelligent Learning Environment for Advanced Cardiac Life Support

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Resuscitation from clinical cardiac arrest is complex and often takes several years to learn. This paper describes an intelligent simulation-based tutor for ACLS which increases students' opportunity to practice before, during and after the ACLS course, thus bridging the gap between studying theory and didactic textbook material and working with patients. Sophisticated reasoning about student performance, compared to an expert model, distinguishes this system from other computerized instruction systems. Intelligence in the tutor allows the system to make the simulation dynamically adaptive to focus on areas where the student's learning needs are greatest. A formative evaluation with two classes of fourth year medical students suggested that the tutor was helpful, realistic and effective. Positive reactions and strong student involvement with the simulation suggest that this simulation-based tutor may improve learning and retention while decreasing anxiety for most students.

INTRODUCTION

The field of computer-based education in medicine has produced many high expectations and very few practical systems [1, 2, 3, 4]. Two reasons are frequently given for this situation. 1) Many medical decision support medical systems claim that they can also be used as educational tools [5]. In such cases, the research paper frequently ends with the sentence "In addition, application <X> can be used for training of its users". However, the necessary explanation facilities for application <X> are frequently missing, or unusable while working with a patient [5]. 2) Medical educational systems system often lack a foundation in educational theories [3].

In fact, education based upon systems that solve a user's problems is in contradiction with psychological theories on knowledge and skills, job satisfaction, self-esteem and development of relations between personnel [6]. The health care system as a whole is better off by empowering personnel to do a better job instead of giving them powerful tools that solve their complicated cognitive activities [5].

In addition, Guidon [7] showed that adapting a medical expert system to learning was inappropriate, since expert systems are hard to understand or explain, and furthermore the expert reasoning was inconsistent with a medical student's reasoning. This has led to a model of diagnostic thinking which involves several levels of clinical problem solving [8].

Applications of artificial intelligence in training have shown promising results. Learning time has been shown to be reduced by 1/2 to 1/3 as compared to classroom training. One system in the field of aviation industry resulted in trainees who spent 20-25 hours working with a system becoming as proficient in troubleshooting a complex test station as technicians who had been on the job for 4 years or longer [9]. Another successful industrial application related to diagnosis and troubleshooting is the Recovery Boiler Tutor in which personnel were taught to handle accidents and emergencies in complex equipment for regulating paper mill industries [10].

Computer modeling techniques are especially effective in medical education, where the "patient" can be simulated with clinical response determined by model parameters. This paper describes the current state of our work using artificial intelligence and pedagogical techniques to develop medical training systems and methodologies for developing a series of training systems. The distinguishing aspect of this system is the ability to evaluate student comprehension and performance on more than 20 topics and to dynamically adjust the simulation in support of the learning needs of the student. ACLS proved to be a good starting point because it involved both modeling arrythmias and the interactions of the student.

Sudden cardiac arrest remains a leading cause of death world wide despite efforts at preventive education. Confidence, leadership and effective communication are major aspects of good ACLS performance. Leadership in resuscitation efforts is generally taught during a "megacode" session provided by a human expert who simulates the condition of a dying patient. Individual students typically have a chance to "run" the resuscitation only once or twice during a two day course. The leader must give unambiguous and timely commands in such a way as to maintain control of a high pressure chaotic situation. The Cardiac Tutor was designed to provide practical experience which supports development of these abilities.

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Our intention is to continue to model the human body, moving on to other systems, such as the respiratory system and trauma care. The predictive capabilities of such models will serve as a basis for additional medical educational systems.

METHODS

The research was conducted both in the Emergency Room at the Medical Center of, and in the Department of Computer Science at the University of Massachusetts. Specifically the steps were to:

- Identify the knowledge;
- Model and implement the simulation;
- Implement medical cases and student model;
- Modify the system based on prototype tests; and
- Evaluate the system with medical students.

Identify the knowledge
The simulated cardiac patient was designed to support practice of algorithms recommended by the Advanced Cardiac Life Support (ACLS) standards interpreted according to interviews with emergency medicine specialists and practicing internists in the Emergency Room at the Medical Center. The process of acquiring sufficient knowledge and skills through practical experience was identified as a primary shortcoming of existing training methods [11]. In order to address this shortcoming, the physicians identified:

- relevant arrythmias, indicated recommended medications or interventions, solved sub-problems for each arrhythmia, and selected possible next arrythmias,
- appropriate explanations and reasoning for each medically recommended step,
- a variety of relevant and reasonable cases for demonstration including rarely occurring cases, and
- appropriate student feedback.

Development of the knowledge base began with the published ACLS standards; domain experts provided the knowledge necessary to discern various levels of correct and incorrect actions as well as the likelihood of various patient responses to actions in each medical state. The system was designed to the 1987 ACLS standards [12], and adapted to the 1992 standards [13] when they were adopted, illustrating the potential for knowledge-based systems to be responsive to advances in scientific or clinical understanding.

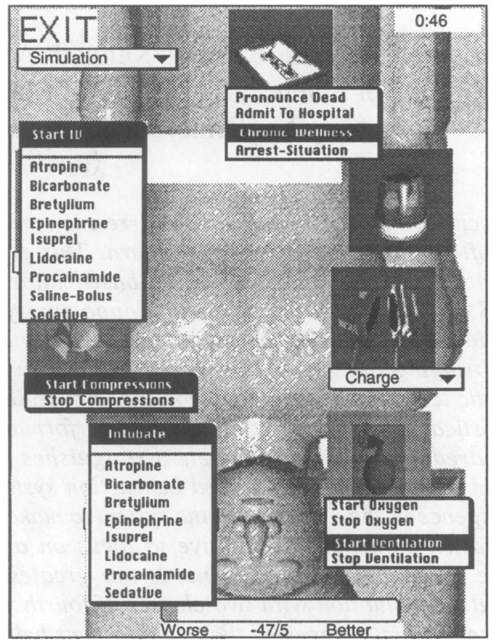

Figure 1. The Cardiac Arrest Simulation.

Model and Implement the Simulation
Most simulations in multimedia programs for medical education perform only simple calculations about high-level physiological behavior [14]. Our work included developing physiological and functional models of cardiac rhythms within a simulation (technically, these were encoded using process-model discrete-event techniques). The simulation described the relationship among arrythmias, (e.g. ventricular fibrillation, ventricular tachycardia, asystole and bradycardia), medications, (e.g., bretylium, atropine, and lidocaine) interventions, (e.g., compressions, electric therapy, and ventilation, Figure 1), and measurements (e.g., ECG trace, pulse and respiration, Figure 2). The system explicitly linked the student's interventions with the physiological behavior of the heart and medical interactions with the arrhythmia. The system reacted in real time to applications of medication and other therapeutic interventions, moving between arrythmias as appropriate.

During the simulation, a current patient ECG trace, pulse rate, blood pressure, mental state and plasma pH was displayed and the simulation calculated an acute wellness score for that state, Figure 2, 3, 4. Recent past states are recalled, as well as a construct of chronic wellness, allowing predictive accuracy. Once an arrhythmia occurred (presented as a waveform generated cardiogram), the simulation reacted to clinical "reality" as determined by the patient state and the actions chosen by the user. User choice was compared with recommended actions, as determined by ACLS standards.

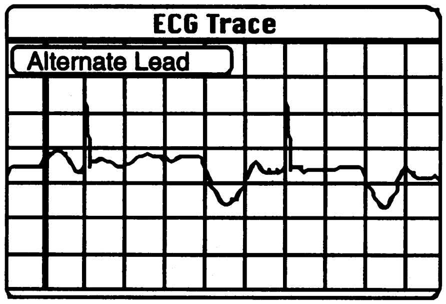

Figure 2. Simulated Ventricular Fibrillation with Pacemaker Capture Spikes.

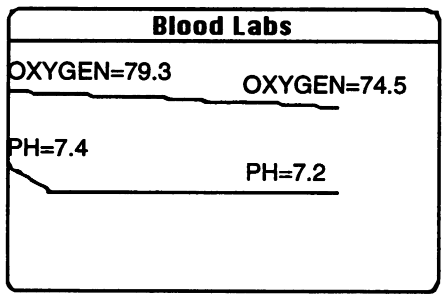

Figure 3. Blood Labs Monitor.

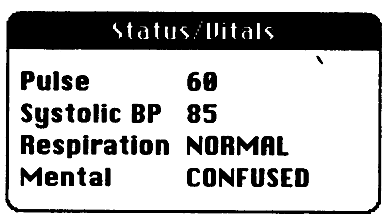

Figure 4. Status of a Confused Patient.

Implement Medical Cases and Student Model
The simulation generated patient cardiac arrythmias. The student learned the problem solving behavior for cardiac arrest by interacting with the tutor. The tutor monitored the student's interaction with the simulated patient, critiqued the student's performance, "explained" both the patient case and the required expert intervention and anticipated alternative expert solutions of the problem The tutor presented new cases based on dynamically changing learning goals. It generated suitable follow-on patient cases customized according to individual student differences and evaluated the student's knowledge, broken down into knowledge of distinct arrythmias, medications, and interventions. The tutor evaluated both the simulated arrhythmia and the student's previous performance to determine the real-time simulation sequence.

A student model was implemented to analyze the student's knowledge and skills at any moment during use of the tutor. Dynamic observations of the student's performance on more than 20 topics were recorded. The tutor recorded the number of experiences with and the number of errors and correct actions realized by the student for each arrhythmia, intervention and medication. It calculated the student's comprehension of each topic and the priority of presenting that topic again based on the student's comprehension and the topic's importance.

The simulation was biased to reach goal states -- or medical topics that are predicted to give the student the most opportunity to learn. Figures 5 and 6 show how the system dynamically alters the probability of state transitions in the simulation model to increase goal-directed behavior without entirely eliminating the probabilistic nature of the model. Notice how the probability of moving from VFIB into BRADY changes. This bias mechanism enabled the simulation to change to a new state based on the student's knowledge and learning needs. The student model integrated medical and pedagogical constraints to determine a current set of tutoring goals, their relative priority and plans for achieving them. This reduced the time each student spent to reach a given skill, balancing the efficiency of goal-directed simulation with the psychological requirement to give the student unexpected clinical problems [15].

The tutor classified many specific student errors and generated feedback specifically informing the student about how individual actions fail to conform with the established protocols. The system ensured that every recommendation it made was in fact possible in the current situation and conformed to some interpretation of the student's actions applied to the protocols [16]. Extended feedback was provided to the student during retrospective analysis following each simulation.

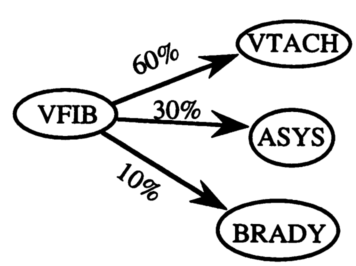

Figure 5. Clinical Probability.

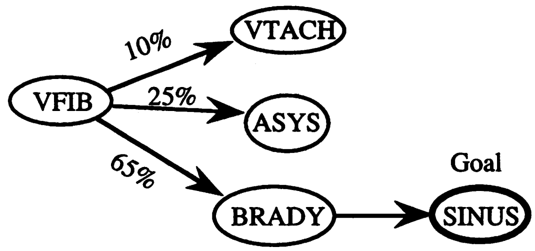

Figure 6. Improbable Clinical Sequence.

Modify The System Based On Prototype Tests
The system was developed with planning technology used to monitor the student and offer appropriate critique. The tutor was presented to the user in a graphical interface with audio as well as visual and animation presentations. The user operated the tutor with a pointing device; no typing was required.

The system was used by resident physicians and domain experts several times in order to identify deficiencies in either the knowledge base or the interface. All components were tested and deficiencies repaired. After development, the tutor was introduced to medical students.

Evaluate The System With Medical Students
The tutor was introduced to two classes of fourth year medical students in a regular ACLS course. The class group was selected to minimize clinical impact of the study; the students would not lead actual resuscitation efforts until completing another ACLS course. Students were randomized to interact with either the traditional human instructor or with the tutor during the same period allotted for megacode practice during the first day of a standard ACLS course. Instructors and students completed evaluation forms after the megacode test. Results of the study are informal observations without quantitative data.

The students became deeply engaged in trying to "save" the simulated patient and displayed an emotional commitment to the effort. Comments from the tutor provided a strong motivation for students to critically review their own knowledge. Several students working with the system began active discussions of the medical situation and often referred back to the ACLS manual. Student conversation clearly contributed to reflective thought and the situated discussion helped students explore and understand fundamental concepts in the domain. Students found the simulation motivating and medically realistic. They did not object to the improbable ordering of topics, which improved learning efficiency.

In contrast, the students being taught by a human instructor were much more passive and appeared reluctant to express their opinions or reasoning. However, the human instructor was better able to probe the limits of a student's understanding verbally and could answer a much wider range of questions than the computerized system.

RESULTS

Students generally made positive comments about the tutor and those with more clinical confidence appeared more willing to try the system and also worked longer with the system. Some students gave up their lunch break to spend more time with the tutor, and many voiced interest in having the system available for further practice. An instructor, with little computer background, completed his first simulation without errors, demonstrating that computer experience is not necessary to work with the tutor.

Group discussions around the tutor suggest that the system may be most effective when installed to promote group, rather than individual use. The computer feedback generated active discussion and directed review of the text in a collaborative manner.

Positive aspects of the tutor were its portability, accurate reflection of clinical reality, student monitoring and availability. Adaptation to individual students was a strong asset, since a system limited to a number of canned text or option cases would rapidly lose educational value in a setting with hundreds of students where the flow of "case 4" becomes readily known.

The negative aspects include the lack of training in human leadership skills and the risk-adverse perception by students that practice on a computer reduced their chances at passing the megacode test solely due to reduced interaction with the testing instructor. We attribute this risk-aversion to the experimental setup rather than to the program.

DISCUSSION

An iterative development process was used to build a simulation-based intelligent learning environment for teaching ACLS. Practicing internists, physicians and students were regularly interviewed and asked to test the tutor in order to guide further system development. Medical education systems benefit from such an iterative development process because the exact knowledge to be taught is not initially known and because extensive user-interaction and feedback is required for interface design.

Unlike typical teaching systems, this tutor did not simply classify actions as right or wrong. Rather, it responded to idiosyncratic student activity, e.g., by suggesting that the wrong protocol was being followed in one action when the user chose to defibrillate a patient with normal sinus rhythm. Dynamic feedback was based on real-time comparisons between user and expert actions in the context of the simulation. Knowledge was used to determine which user actions matched expert actions, whether actions were totally or partially correct and to identify expected actions that were not performed (such as calling for everyone to "stand clear" just before defibrillation). Because actions were compared to a richly structured description of the system's model of expert performance, the tutor could detect partial errors, e.g., giving the correct medicine in an incorrect dose.

CONCLUSION

This tutor is distinguished by its ability to individualize simulation behavior using an evaluation of student performance which is automatically derived using knowledge-based reasoning techniques. The tutor analyzed student mistakes and generated corrective feedback. It provided valuable practice, which will become more valuable as tutors are better able to explain *how* and *why* the student should have performed certain things and *why not* use certain other actions.

While promising, the megacode tutor should be considered only a model for future work in this area. The tutor appears to result in learning comparable to one hour of teaching from a human tutor in a regularly scheduled class. Considerable improvements in this area are possible, requiring further research into knowledge representation and explanation systems.

The incorporation of intelligent reasoning in a complex simulation model has the potential to help explore the accuracy of guidelines such as ACLS algorithms and to improve care in ways far beyond the education of medical professionals. For instance, it may provide a foundation for documentation and quality improvement tools and perhaps for a new generation of diagnostic aids.

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